Early Predictor for Student Success Based on Behavioural and Demographical Indicators

Import libraries

In [234…
```
import zipfile
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

Load data

In [235…
```
zf = zipfile.ZipFile('./data.zip')
student_info = pd.read_csv(zf.open('studentInfo.csv'))
student_vle = pd.read_csv(zf.open('studentVle.csv'))
student_assessment = pd.read_csv(zf.open('studentAssessment.csv'))
student_registration = pd.read_csv(zf.open('studentRegistration.csv'))
assessments = pd.read_csv(zf.open('assessments.csv'))
```

Basic information about modules, first assessments and number of registered students

In [236…
```
# Get information about first day assessments
basic_info = assessments.filter(items=['code_module', 'code_presentation', 'date'])
basic_info = basic_info.groupby(['code_module', 'code_presentation']).min()
basic_info = pd.merge(basic_info, assessments, on=['code_module', 'code_presentation', 'date'],
                             how='inner').filter(items=['code_module', 'code_presentation', 'id_assessment', 'date'])

# Get total number of registered students for each module
registrations = student_registration.filter(items=['code_module', 'code_presentation', 'id_student']).groupby(
    ['code_module', 'code_presentation']).count().reset_index()
basic_info.insert(4, "number of registered students", registrations['id_student'])
basic_info
```

Out[236…

	code_module	code_presentation	id_assessment	date	number of registered students
0	AAA	2013J	1752	19.0	383
1	AAA	2014J	1758	19.0	365
2	BBB	2013B	14984	19.0	1767
3	BBB	2013J	14996	19.0	2237
4	BBB	2014B	15008	12.0	1613
5	BBB	2014J	15020	19.0	2292
6	CCC	2014B	24286	18.0	1936
7	CCC	2014J	24295	18.0	2498
8	DDD	2013B	25341	23.0	1303
9	DDD	2013J	25348	25.0	1938
10	DDD	2014B	25355	25.0	1228
11	DDD	2014J	25362	20.0	1803
12	EEE	2013J	30709	33.0	1052
13	EEE	2014B	30714	33.0	694
14	EEE	2014J	30719	33.0	1188
15	FFF	2013B	34860	19.0	1614
16	FFF	2013J	34873	19.0	2283
17	FFF	2014B	34886	24.0	1500
18	FFF	2014J	34899	24.0	2365
19	GGG	2013J	37415	61.0	952
20	GGG	2014B	37425	61.0	833
21	GGG	2014J	37435	61.0	749

Data preparation

In [237…
```
clicks_before_start = student_vle[student_vle['date'] < 0]

# Merge student_info and student_registration tables to get registration_date
df1 = pd.merge(student_info, student_registration, how='left', on=['id_student', 'code_module', 'code_presentation'])

# Merge previous table with basic_info that was created earlier to get first assessment days and ids
df2 = pd.merge(df1, basic_info, on=['code_module', 'code_presentation'], how='left')

# Merge previous table with student assessment to find student's scores on their first assessments
df3 = pd.merge(df2, student_assessment, on=['id_assessment', 'id_student'], how='left')

# Merge previous table with clicks_before_start table that was created earlier
data = pd.merge(df3, clicks_before_start, on=['id_student', 'code_module', 'code_presentation'], how='left')

# Keep only columns that are needed later
data = data.filter(['code_module', 'code_presentation', 'id_student', 'score', 'highest_education', 'sum_click',
                    'date_registration', 'age_band',
                    'disability', 'gender', 'num_of_prev_attempts', 'final_result'])
data.fillna(value=0, inplace=True)

# Get number of clicks before course start
data = data.groupby(
    ['code_module', 'code_presentation', 'id_student', 'score', 'highest_education', 'date_registration',
     'age_band', 'disability', 'gender', 'num_of_prev_attempts', 'final_result']).sum().reset_index()

# Get the final dataframe that will be used
data = data[['id_student', 'gender', 'highest_education', 'age_band', 'num_of_prev_attempts', 'disability', 'score',
             'date_registration', 'sum_click', 'final_result']]
data.rename(columns={'score': 'first_assignment', 'sum_click': 'clicks_before_start',
                     'num_of_prev_attempts': 'previous_attempts', 'age_band': 'age'}, inplace=True)
data.head()
```

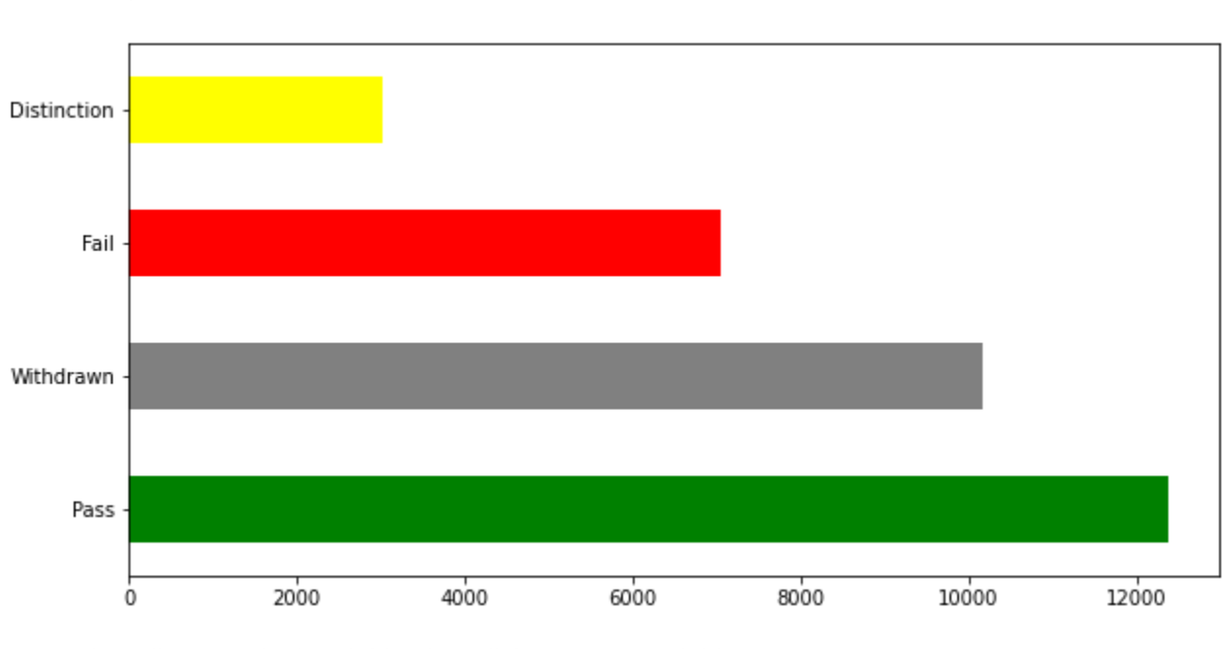
Out[237…

	id_student	gender	highest_education	age	previous_attempts	disability	first_assignment	date_registration	clicks_before_start	final_result
0	11391	M	HE Qualification	55<=	0	N	78.0	-159.0	98.0	Pass
1	28400	F	HE Qualification	35-55	0	N	70.0	-53.0	215.0	Pass
2	30268	F	A Level or Equivalent	35-55	0	Y	0.0	-92.0	102.0	Withdrawn
3	31604	F	A Level or Equivalent	35-55	0	N	72.0	-52.0	169.0	Pass
4	32885	F	Lower Than A Level	0-35	0	N	69.0	-176.0	295.0	Pass

Number of students in 4 categories based on their final results.

In [238…
```
counts = student_info['final_result'].value_counts()
counts.plot.barh(x=['Pass', 'Withdrawn', 'Fail', 'Distinction'], color=['green', 'gray', 'red', 'yellow'],
                 figsize=(10, 5))
```

Out[238…
```
<AxesSubplot:>
```



Converting all categorical variables into dichotomous variables.

In [239…
```
education_mapping = {
    'No Formal quals': 0,
    'Lower Than A Level': 0,
    'A Level or Equivalent': 0,
    'HE Qualification': 1,
    'Post Graduate Qualification': 1
}

age_mapping = {
    '0-35': 0,
    '35-55': 1,
    '55<=': 1
}

grade_mapping = {
    'Withdrawn': 0,
    'Fail': 1,
    'Pass': 2,
    'Distinction': 3
}

gender_mapping = {
    'F': 1,
    'M': 0
}

disability_mapping = {
    'N': 0,
    'Y': 1
}

data['highest_education'] = data['highest_education'].map(education_mapping)
data['age'] = data['age'].map(age_mapping)
data['final_result'] = data['final_result'].map(grade_mapping)
data['gender'] = data['gender'].map(gender_mapping)
data['disability'] = data['disability'].map(disability_mapping)

data.head()
```

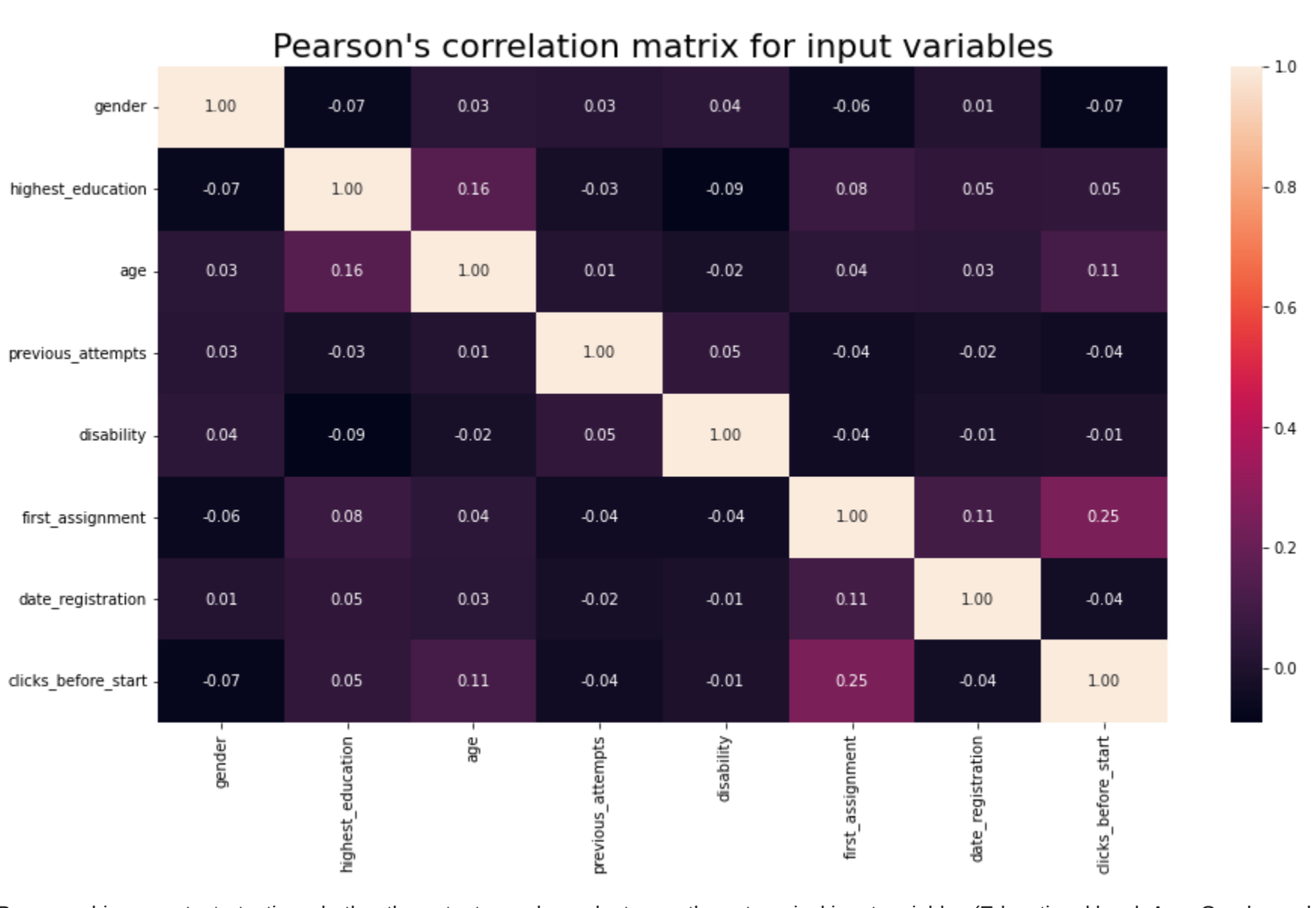
Out[239…

	id_student	gender	highest_education	age	previous_attempts	disability	first_assignment	date_registration	clicks_before_start	final_result
0	11391	0	1	1	0	0	78.0	-159.0	98.0	2
1	28400	1	1	1	0	0	70.0	-53.0	215.0	2
2	30268	1	0	1	0	1	0.0	-92.0	102.0	0
3	31604	1	0	1	0	0	72.0	-52.0	169.0	2
4	32885	1	0	0	0	0	69.0	-176.0	295.0	2

Pearson's correlation matrix for input variables.

In [240…
```
plt.figure(figsize=(15, 8))
corr = data.drop(columns=['id_student', 'final_result'], inplace=False).corr(method='pearson')
corr_heatmap = sns.heatmap(corr, annot=True, fmt='.2f')
corr_heatmap.set_title('Pearson\'s correlation matrix for input variables', fontdict={'fontsize': 22})
```

Out[240…
```
Text(0.5, 1.0, "Pearson's correlation matrix for input variables")
```



Pearson chi-square test - testing whether the output was dependent upon the categorical input variables (Educational level, Age, Gender and Disability).

In [241…
```
from scipy.stats import chi2_contingency

test_df = pd.DataFrame(index=['statistic', 'p-value'])

for var in ['highest_education', 'age', 'gender', 'disability']:
    obs = pd.crosstab(data[var], data['final_result'])
    chi2, pval, _, __ = chi2_contingency(obs)
    test_df.insert(0, var, [chi2, pval])
test_df
```

Out[241…

	disability	gender	age	highest_education
statistic	1.384540e+02	16.530150	2.068228e+02	3.829559e+02
p-value	8.143196e-30	0.000883	1.415187e-44	1.088496e-82

Initialize lambdas that will be later used for one-vs-rest models.

In [242…
```
withdrawn_lambda = lambda x: 1 if x == 0 else -1
fail_lambda = lambda x: 1 if x == 1 else -1
pass_lambda = lambda x: 1 if x == 2 else -1
distinction_lambda = lambda x: 1 if x == 3 else -1
```

Generate training and testing sets.

In [251…
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(data[['first_assignment', 'highest_education', 'age', 'gender', 'previous_attempts', 'disability', 'clicks_before_start', 'date_registration']],
                                                    data['final_result'], test_size=0.3, random_state=2)

y_train_withdrawn = y_train.map(withdrawn_lambda)
y_test_withdrawn = y_test.map(withdrawn_lambda)

y_train_fail = y_train.map(fail_lambda)
y_test_fail = y_test.map(fail_lambda)

y_train_pass = y_train.map(pass_lambda)
y_test_pass = y_test.map(pass_lambda)

y_train_distinction = y_train.map(distinction_lambda)
y_test_distinction = y_test.map(distinction_lambda)

y_trains = [y_train_withdrawn, y_train_fail, y_train_pass, y_train_distinction]
y_tests = [y_test_withdrawn, y_test_fail, y_test_pass, y_test_distinction]
```

Decision Tree

In [252…
```
from sklearn.tree import DecisionTreeClassifier

decision_trees = [DecisionTreeClassifier(class_weight='balanced', min_samples_split=10) for i in range(4)]

for index, tree in enumerate(decision_trees):
    tree.fit(X_train, y_trains[index])
```

Random Forest

In [253…
```
from sklearn.ensemble import RandomForestClassifier

random_forests = [RandomForestClassifier(n_jobs=-1, class_weight='balanced', bootstrap=False, min_samples_split=10) for i in range(4)]

for index, forest in (enumerate(random_forests)):
    forest.fit(X_train, y_trains[index])
```

Bayesian Additive Regression Trees (BART)

In [254…
```
from bartpy.sklearnmodel import SklearnModel

barts = [SklearnModel(n_burn=200, n_chains=2, n_samples=200, n_trees=50, alpha=0.9, beta=1.5) for i in range(4)]

for index, bart in enumerate(barts):
    bart.fit(X_train, y_trains[index])
```

Results

In [255…
```
from sklearn.metrics import accuracy_score, precision_score, f1_score, recall_score, confusion_matrix

results = []

for model, test in zip(decision_trees + random_forests, y_tests * 2):
    for score in [precision_score, recall_score, f1_score, accuracy_score]:
        results.append(score(y_pred=model.predict(X_test), y_true=test))

for model, test in zip(barts, y_tests):
    for score in [precision_score, recall_score, f1_score, accuracy_score]:
        results.append(score(y_pred=[1 if res >= 0 else -1 for res in model.predict(X_test)], y_true=test))

split = np.array_split(results, 3)

multi = pd.MultiIndex.from_product(
    [['Withdrawn', 'Fail', 'Pass', 'Distinction'], ['Precision', 'Recall', 'F1', 'Accuracy']],
    names=['Final result', 'Metric'])

results = pd.DataFrame(index=multi, columns=['Decision tree', 'Random forest', 'BART'],
                       data={'Decision tree': split[0], 'Random forest': split[1], 'BART': split[2]})
results
```

Out[255…

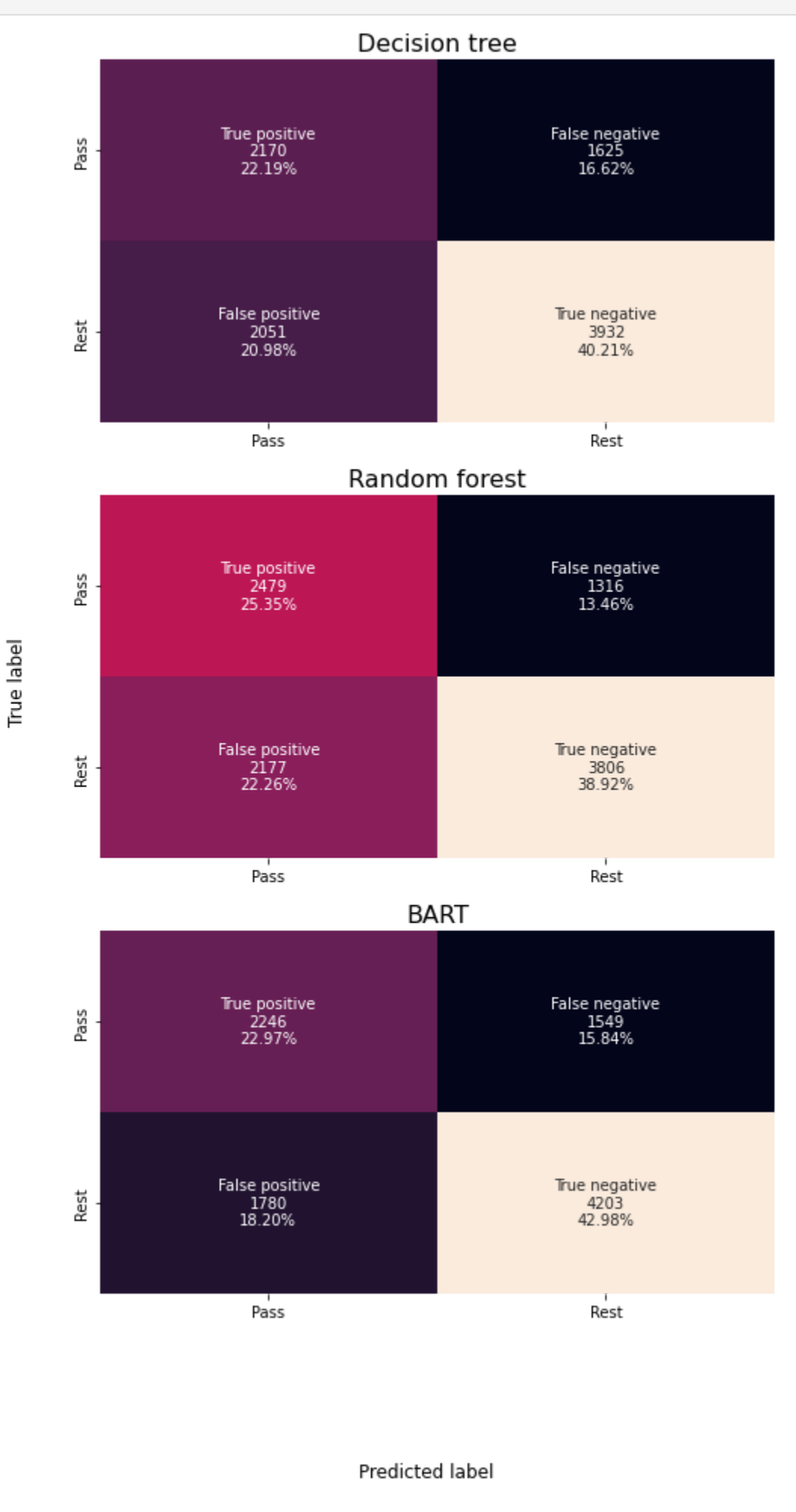
		Decision tree	Random forest	BART
Final result	**Metric**			
Withdrawn	Precision	0.495504	0.655797	0.774590
	Recall	0.664212	0.605959	0.569468
	F1	0.567587	0.629894	0.656377
	Accuracy	0.690837	0.782471	0.817856
Fail	Precision	0.254051	0.286907	0.333333
	Recall	0.416311	0.309625	0.002845
	F1	0.315544	0.297834	0.005642
	Accuracy	0.610452	0.685109	0.783698
Pass	Precision	0.514096	0.532431	0.557874
	Recall	0.571805	0.653228	0.591831
	F1	0.541417	0.586676	0.574351
	Accuracy	0.624054	0.642769	0.659542
Distinction	Precision	0.188446	0.257562	0.722222
	Recall	0.378805	0.316798	0.014656
	F1	0.251685	0.284125	0.028729
	Accuracy	0.795664	0.855185	0.910104

Fail-vs-rest i Distinction-vs-rest klasifikatori iz nekoga nepoznatog razloga daju puno lošije rezultate od ostalih klasifikatora, a ne bi trebali.

Confusion matrix for Pass-vs-rest.

In [256…
```
fig, axs = plt.subplots(3, 1, figsize=(8, 15))
fig.supxlabel('Predicted label')
fig.supylabel('True label')
k = 1
titles = ['Decision tree', 'Random forest', 'BART']

for index, model in enumerate([decision_trees[2], random_forests[2], barts[2]]):
    cf_matrix = confusion_matrix(y_true=y_tests[2], y_pred=model.predict(X_test) if index != 2 else
    [1 if res >= 0 else -1 for res in model.predict(X_test)], labels=[1, -1])
    group_names = ['True positive', 'False negative', 'False positive', 'True negative']
    group_counts = ["{0:0.0f}".format(value) for value in cf_matrix.flatten()]
    group_percentages = ["{0:.2%}".format(value) for value in cf_matrix.flatten() / np.sum(cf_matrix)]
    labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in zip(group_names, group_counts, group_percentages)]
    labels = np.asarray(labels).reshape(2, 2)
    plt.subplot(3, 1, k)
    plt.title(titles[index], fontdict={'fontsize': 16})
    df_cm = pd.DataFrame(cf_matrix, columns=['Pass', 'Rest'], index=['Pass', 'Rest'])
    sns.heatmap(df_cm, annot=labels, fmt='', cbar=False)
    k += 1
```



Performance of the algorithms for the Distinction-vs-rest classification task.

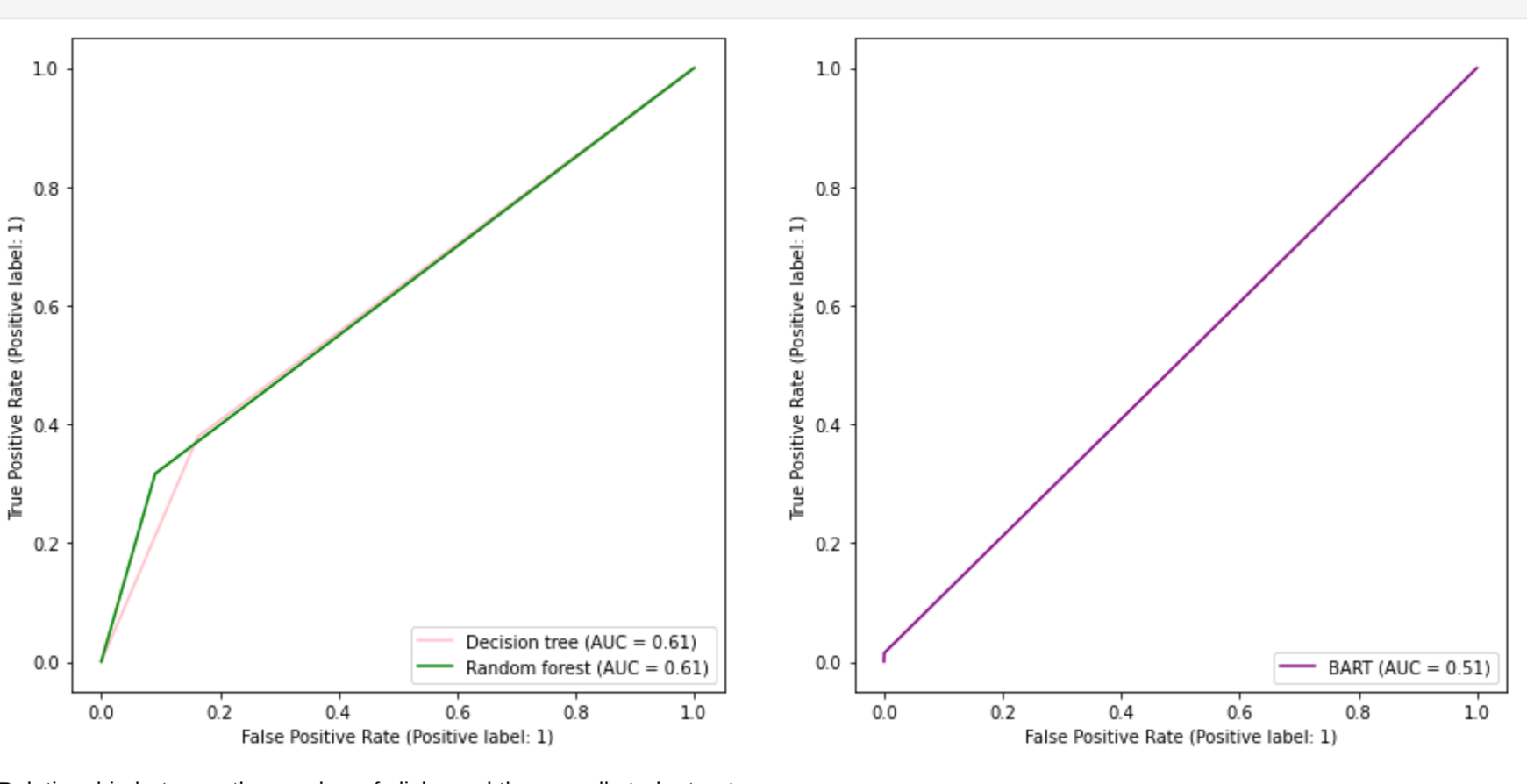
In [257…
```
from sklearn.metrics import RocCurveDisplay

fig, axs = plt.subplots(1, 2, figsize=(15,7))

decision_tree_roc = RocCurveDisplay.from_predictions(y_true=y_tests[3], y_pred=decision_trees[3].predict(X_test), name='Decision tree')
random_forest_roc = RocCurveDisplay.from_predictions(y_true=y_tests[3], y_pred=random_forests[3].predict(X_test), name='Random forest')
bart_roc = RocCurveDisplay.from_predictions(y_true=y_tests[3], y_pred=[1 if res >= 0 else -1 for res in barts[3].predict(X_test)], name='BART')

decision_tree_roc.plot(ax=axs[0], color='pink')
random_forest_roc.plot(ax=axs[0], color='green')
bart_roc.plot(ax=axs[1], color='purple')

for _ in range(3):
    plt.close()
```



Relationship between the number of clicks and the overall student outcome.

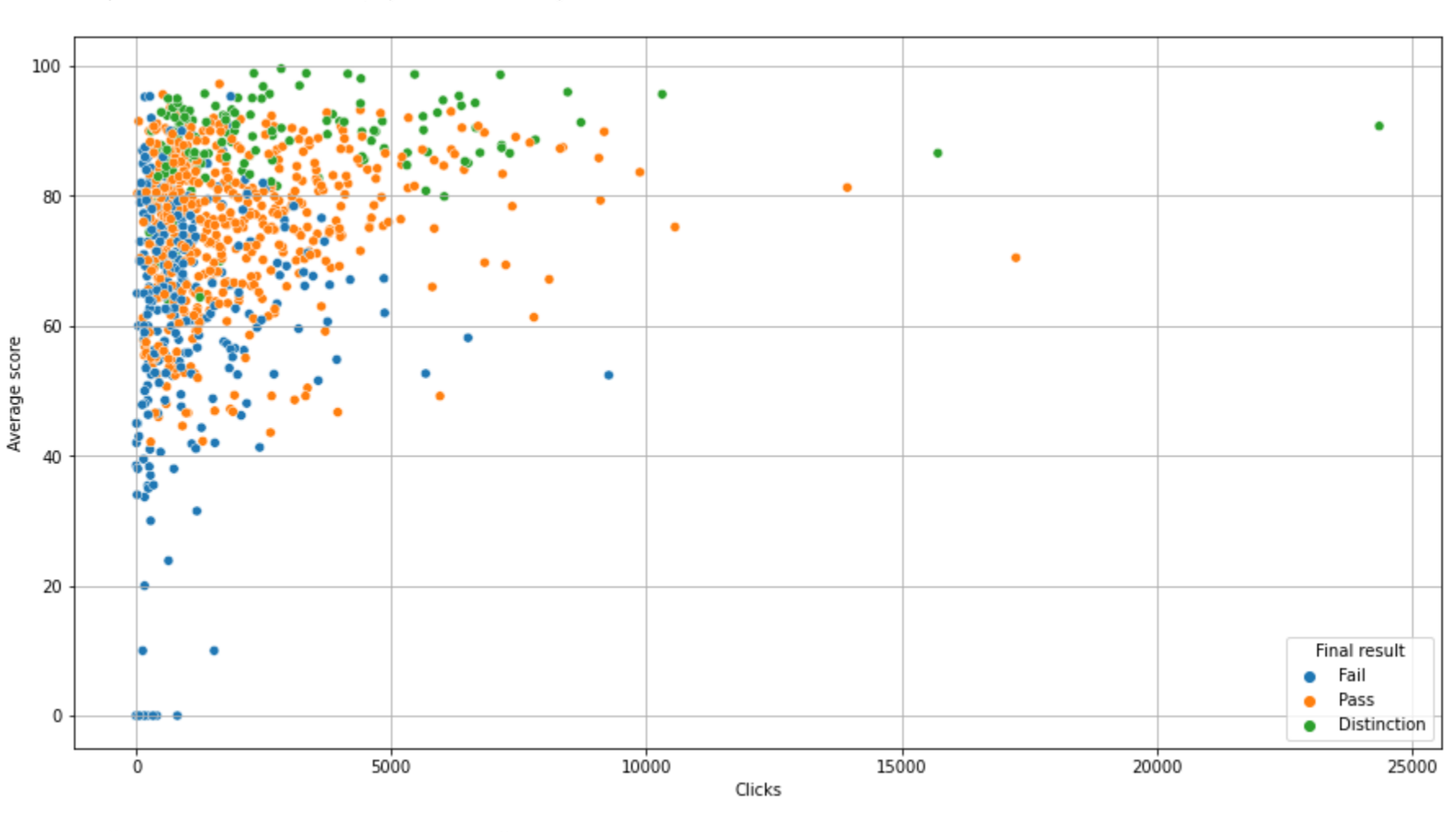
In [250…
```
# Merge student_info with student_assessment to get average score
table = pd.merge(student_info, student_assessment, how='left', on=['id_student'])[['id_student', 'score', 'final_result']]
table.fillna(value=0, inplace=True)
table = table.groupby(by=['id_student', 'final_result']).mean().reset_index()

# Merge previous table with student_vle to get total amount of clicks
table = pd.merge(table, student_vle, how='left', on=['id_student'])[['id_student', 'final_result', 'score', 'sum_click']]
table.fillna(value=0, inplace=True)
table = table.groupby(by=['id_student', 'final_result', 'score']).sum().reset_index()

table = table[table['final_result'] != 'Withdrawn']
table.rename(columns={'score': 'Average score', 'final_result': 'Final result', 'sum_click': 'Clicks'}, inplace=True)
table = table.sample(1000)

plt.figure(figsize=(15, 8))
plt.grid()
sns.scatterplot(data=table, x='Clicks', y='Average score', hue='Final result')
```

Out[250…
```
<AxesSubplot:xlabel='Clicks', ylabel='Average score'>
```



Vrsta istraživanja prema svrsi: primjenjeno istraživanje

- Želi se otkriti obrazac uspjeha u učenju kako bi se moglo na vrijeme identificirati oni koji bi mogli imati poteškoće.

Vrsta istraživanja prema dubini: istraživačno (explanatory) istraživanje

- Postavlja temeljne okvire i hipoteze o ključnim socio-ekonomskim i demografskim značajkama koje utječu na uspjeh pojedinca za daljnje, dublje analize.

Vrsta istraživanja prema vrsti korištenih podataka: kvantitativno istraživanje

- Podaci su kvantitativni te se koriste statističke metode i metode strojnog učenja kako bi se objasnio i predvidio uspjeh polaganja tečaja.

Vrsta istraživanja prema stupnju manipulacije varijablama: promatračko istraživanje (opservacijsko, deskriptivno, neeksperimentalno)

- Nema intervencije istraživača, već se koriste podaci koji su skupljeni u prirodnom okruženju.

Vrsta istraživanja prema vrsti zaključka: hipotetičko-deduktivno istraživanje

- U ovom istraživanju promatra se stvarnost te skupljaju podaci kako bi se postavila hipoteza da socio-ekonomske i demografske karakteristike pojedicna utječu na njihov uspjeh, zatim se pomoću modela strojnog učenja pokušavaju izoliati sve one karakteristike pomoću kojih je moguće zaključiti i predivdjeti buduće uspjehe i neuspjehe.

Vrsta istraživanja prema vremenu provedbe: studija presjeka ili sinkrono istraživanje

- Promatraju se određeni trenutci u istraživanju, konkretno početak tečaja i kraj tečaja. Nije naglasak na tome kako se pojedinci ponašaju tijekom tečaja, već što možemo reći o krajnjom rezultatu tečaja (prolaz, pad itd.) na temelju podataka koje imamo na početku, prije početka tečaja. Ne prate se kako se varijable mijenjaju tijekom tečaja jer većina njih (socio-ekonomske i demografske) su konzistentne cijelo vrijeme.

Vrsta istraživanja prema izvoru informacija: sekundarno istraživanje

- Izvor informacija dolazi iz vanjskih izvora, OULAD (Open University Learning Analytics Dataset) te se želi identificirati obrasci i trendovi koji upućuju na drugačije ishode završetka tečaja.

Vrsta istraživanja prema načinu prikupljanja podataka: dokumentarno istraživanje

- Rad koristi vanjsku bazu podataka koji su drugi istraživači prikupili, a za te istraživače možemo reći da su radili terensko istraživanje jer su skupljali podatke sa izvora (tečaja).

Metode prikupljanja podataka: opservacijsko istraživanje

- Skupljeni podaci su dobiveni opservacijom, tj. promatranju stvari onako kako se događaju, bez ikakve intervencije. Radi se o sistematskom promatranju gdje se skupljaju kvantitavni objektivni podaci (poput prve ocjene ili broj klikova prije početka tečaja).

Istraživačka etika:

Na ovoj poveznici nalazi se kratak osvrt na način prikupljanja podataka. Najbitnije stvari su citirane u nastavku.

- sudionici su zaštićeni od fizičkih i psihičkih ozlijeda
- sudionici su anonimni (izbačeni su bilo kakve privatne informacije koje bi mogle identificirati studente)

> The first step removed private information about students and modules. This includes the social security number, dates of birth and unique identifiers used at the OU for students. Module names have been replaced by semantic-free symbols and all temporal information has been expressed in relative terms with respect to the presentation start. In addition, all numeric identifiers (i.e., student_id, code_module, etc.) have been reassigned and completely randomised.

- povjerljivi podaci nisu uključeni u javni dataset